Rapid temporal accumulation in spider fear: Evidence from Hierarchical Drift Diffusion Modelling

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Abstract

Fear can distort our sense of time – making time seem slow or even stand still. Here, I used Hierarchical Drift Diffusion Modelling (HDDM; Vandekerckhove, Tuerlinckx, & Lee, 2008, 2011; Wiecki, Sofer, & Frank, 2013) to test the idea that temporal accumulation speeds up during fear. Eighteen high fearful and twenty-three low fearful participants judged the duration of both feared stimuli (spiders) and non-feared stimuli (birds) in a temporal bisection task. The drift diffusion modelling results support the main hypothesis. In high but not low fearful individuals evidence accumulated more rapidly toward a long duration decision - drift rates were higher – for spiders compared to birds. This result and further insights into how fear affects time perception would not have been possible based on analyses of choice proportion data alone. Further results were interpreted in the context of a recent two-stage model of time perception (Balci & Simen, 2014). The results highlight the usefulness of diffusion modelling to test process-based explanations of disordered cognition in emotional disorders.

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In moments of high fear people often report that time is slowing down or even standing still. A distorted sense of time for fear-evoking and other emotionally arousing stimuli has been consistently reported in laboratory research. For example, a recent study (Buetti & Lleras, 2012) found that high fearful individuals perceive the duration of spiders as lasting longer than control stimuli. One explanation of this effect is that fear increases the rate at which temporal information accumulates. The novel approach taken here is to use Hierarchical Drift Diffusion Modelling (HDDM; Wiecki et al., 2013) to: 1) test the rapid temporal accumulation hypothesis for feared stimuli 2) provide evidence of how the effects of fear on time perception unfold across time in the context of a recent model of timing (Balci & Simen, 2014).

Studies using the temporal bisection task have shown that time perception is particularly sensitive to the effects of fear-related stimuli. In one study (Grommet et al., 2011), participants completed a training phase in which they learnt to recognise short and long standard durations and, in a test phase, judged whether fear-related and low arousal stimuli from the International Affective Picture System (Lang, Bradley, & Cuthbert, 2005) were more similar in duration to either a long or short duration that they had learnt earlier. Participants judged pictures presented for seven durations presented within both a short (250–1000 ms) and long duration range (400–1600 ms). For both duration ranges, participants judged high fear stimuli as lasting longer than low arousal stimuli. A similar lengthening effect has been recorded for other fear-related stimuli including angry faces (e.g., Gil & Droit-Volet, 2011) and fear-conditioned stimuli (Droit-Volet, Mermillod, Cocenas-Silva, & Gil, 2010; Ogden, Moore, Redfern, & McGlone, 2014). Further studies have shown the effect varies with individual differences including; self-reported fearfulness (Tipples, 2011),

specific phobia (Buetti & Lleras, 2012; Watts & Sharrock, 1984) and anxiety (Bar-Haim, Kerem, Lamy, & Zakay, 2010; Tipples, 2011). For example, spider fearful individuals perceive the duration of spiders to be longer than low arousal stimuli (Buetti & Lleras, 2012). Overall, this set of findings shows that time perception is especially sensitive to distortion due to fear.

But *how* does fear affect time perception? There exist both neural and cognitive models of time perception that could help answer this question (Allman, Teki, Griffiths, & Meck, 2014; for recent reviews see; Grondin, 2010; Muller & Nobre, 2014) . These models differ according to whether they specify either an intrinsic (e.g., Goel & Buonomano, 2014) or a dedicated timing mechanism. The effects of fear on time perception have been interpreted in the context of a popular dedicated timing model - the internal clock model (Gibbon, Church, & Meck, 1984; Rammsayer & Ulrich, 2001; Treisman, Faulkner, Naish, & Brogan, 1990; Treisman, 1963; Zakay & Block, 1997). Internal clock models typically include 1) an arousal-sensitive pacemaker that emits units of time (or pulses) at a specific rate 2) an attention-controlled switch that closes when timing starts and re-opens when time ends and 3) an accumulator where pulses are integrated and perceived time is calculated. The pacemaker increases or decreases in speed. A key prediction concerns the effects of pacemaker speeding over time. If the pacemaker speeds up, then time will be perceived as relatively longer as stimuli durations increase – there will be a multiplicative pattern. For data gathered using the temporal bisection task a multiplicative pattern is indexed by a steeper psychophysical slope for duration - time estimates grow proportionately longer with time. One proposal is that fear (and emotional arousal more generally) speeds the rate of the pacemaker and therefore, a key prediction is that fear will lead to a multiplicative pattern.

Although phobic and unselected individuals consistently overestimate the duration of fear-related stimuli the rate of responding frequently follows an additive rather than

multiplicative pattern across stimulus duration (for recent examples see; Fayolle & Droit-Volet, 2014; Grommet et al., 2011). Within internal clock models, additive effects are thought to reflect the operation of an attention-controlled switch mechanism that closes when timing starts. Therefore, a viable alternative to the pacemaker speeding account is that fear modulates the switch mechanism. However, care is needed when interpreting the absence of process from absence of an interaction because the measurement procedure may lack sensitivity to the predicted effect. For example, a ceiling effect may hide the interaction - the rate of responding may reach an upper limit (a ceiling) sooner for feared stimuli and consequently, the multiplicative pattern is not found.

One way of addressing possible measurement artefact is to include an additional measure that is less susceptible to such effects. Recent results (Tipples, Brattan, & Johnston, 2013) suggest reaction times (RTs) might help shed light on the effects of emotion on time perception. The authors used the bisection task to test for increased neural activation for angry and happy expressions compared to neutral expressions. The results of a recent review (Coull, Cheng, & Meck, 2011) and meta-analyses (Wiener, Turkeltaub, & Coslett, 2010) were used to select regions of interest within a putative time perception network. The authors found that neural response to emotion during timing was strongest within regions of the time perception network when RTs were slowest, at the duration before the arithmetic mean of all stimulus durations. The authors argued that such effects reflect modulation by emotion of the neural structures responsible for temporal decision making because RTs are usually slowest when decisions are most difficult. However, aggregate RTs offer little insight into the processes that might precede a decision making stage. Drift diffusion modelling offers a solution to ceiling effects (Ratcliff, 2014) by modelling both RTs and choice proportion data and also, can shed light on how processes unfold over time. The advantage of drift diffusion modelling over standard RT measures has recently been demonstrated for research into the

effects of emotional stimuli on basic cognitive processes. Specifically, diffusion modelling has been used to uncover: 1) a processing advantage for threat-related words in anxiety (White, Ratcliff, Vasey, & McKoon, 2010) and 2) facilitated processing due to negative distracters in depression (Pe, Vandekerckhove, & Kuppens, 2013). Here, I used diffusion modelling to test for increased temporal accumulation speed due to fear.

- - - - -Insert Figure 1 about here - - - - -

The key idea of the drift diffusion models of two-alternative forced choice data (Ratcliff & McKoon, 2008; Ratcliff, 1978) is that a decision is made based on the sequential accumulation of information over time. As shown in Figure 1, the evidence accumulation process denoted by the drift-rate parameter v, is modelled (with accompanying noise), as following a random walk until a threshold is reached and a decision can be made. In two-alternative forced choice tasks such as the temporal bisection task, the amount of information required for a decision is governed by boundary separating the (short and long) response options. In tasks that emphasize accuracy (e.g., lexical decision), large boundary values indicate conservative response criteria (more information is required for a decision) whereas smaller values indicate more liberal and perhaps impulsive response criteria (less information is required for a decision). Two further parameters are typically calculated from response time and choice proportion (or accuracy) data namely, a starting point z that moves closer to the a particular response threshold when participants demonstrate response biases and non-decision time (T_{er}). The non-decision time parameter T_{er}, is thought to index stimulus encoding and response execution processes. To accommodate different mean correct and mean error RTs, the parameters of inter-trial variability in the drift rate, starting point and non-decision time can also be included in the model.

Recently, researchers (Balci & Simen, 2014) have used diffusion models to understand time perception with data collected using the temporal bisection task. The model

extends the scope of an existing drift diffusion model of time perception (Simen, Balci, deSouza, Cohen, & Holmes, 2011; Simen, Rivest, Ludvig, Balci, & Killeen, 2013) by proposing a sequential drift-diffusion process. Specifically, according to the model proposed by Balci and Simen, decision making in the temporal bisection task is carried out in two stages. In the first stage, temporal information accumulates with accompanying noise until it reaches a single fixed threshold (Simen et al., 2011, 2013). A core assumption of the model is that drift and diffusion during the first stage arise from accumulating Poisson pulses, some excitatory, and some inhibitory (Simen et al., 2011). Time estimates are based on the time taken for the pulses to accumulate toward a single fixed threshold. Information accumulation at this first stage determines the starting point (z) of the follow-up comparison processes that begins at the second stage. The second stage is assumed to start immediately after the offset of the interval (or timing stimulus). During the second stage, the time estimate from the first stage is compared to bisection point - midway between the short and long threshold - where the probability of responding long and short is equal. Participants respond long if the difference exceeds the long threshold and respond short if the difference exceeds the short threshold.

The modelling results reported by Balci and Simen (Balci & Simen, 2014) were in keeping with their two-stage model. First, both drift rates and the starting point parameter (z) increased linearly with stimulus duration. The increase in the drift rate parameter with stimulus duration is direct evidence for an increase the accumulation of temporal information with time – more evidence accrues in favour of the long response with time. The concurrent linear increase in the starting point parameter supports the idea that increased temporal accumulation occurred during initial stimulus exposure. In other experimental tasks, a shift in the starting point parameter might indicate a pre-existing bias for certain response (perhaps through greater reward for that response). However, for data gathered using the bisection task

the two-stage model described by Balci and Simen is best able to explain such a finding. Specifically, during exposure to the stimulus the idea is that evidence accrues in favor of the long response with time and consequently, the starting point parameter shifts towards the long response threshold. Also, there was a linear decrease in non-decision time with time. Again, such a pattern makes sense if it is assumed that during exposure to longer stimulus durations (at the first stage), the drift rate reaches the long threshold and participants have time to prepare a response - effectively reducing their non-decision time.

In the current study, high and low fearful participants judged the duration of both feared stimuli (spiders) and non-feared stimuli (birds) in a temporal bisection task. The central hypothesis was that fear would increase temporal accumulation leading to higher drift rates for feared stimuli. If the effects occur during the presentation of the stimuli then according to the two-stage (Balci & Simen, 2014), higher drift rates will occur concurrently with a shift in the starting point parameter z towards the upper (long) response threshold. Also in keeping with latter model, I predict a linear increase in both drift rates and the starting point parameter z.

Method

Participants

Forty-one psychology undergraduates took part in exchange for a partial course credit. The participants were from a pool of 265 psychology undergraduate students and invited to take part based on their response to an initial screening question: "Are you particularly afraid of spiders?" The sample was composed of 18 high fearful individuals (Mean age = 19; SD = 1.87; 17 females, 1 male) who responded "yes" to initial screening question and a further 23 low fearful individuals (Mean age = 22; SD = 9.71; 16 females, 7 males) who volunteered and responded "no" to the initial screening question. All participants were informed that the experiment involved the presentation of spider images. Validation of the screening question

was carried out by administering the Spider Phobia Questionnaire (SPQ; Klorman, Weerts, Hastings, Melamed, & Lang, 1974) after completion of the experiment. The results of the SPQ validated the assignment of participants to the high and low fearful groups based on the initial screening question. Specifically, the mean score on the SPQ for the high-fearful participants (M = 20.77; SD = 3.35) was higher (F (1, 39), = 268.22, $p < .0001$) than the mean of the low fearful group (M = 4.34; SD = 3.05). The ethical committee of the University of Hull approved the study and informed consent was obtained from all participants.

Stimuli and apparatus

A pink oval used in previous research (Droit-Volet, Brunot, & Niedenthal, 2004) was used in the training phase during which participants learnt to recognize short and long stimuli durations. The stimuli for the test phase consisted of 63 images of spiders that were selected from a recently created picture base (Dan-Glauser & Scherer, 2011) and a further 63 birds collected from the internet. The bird stimuli were selected (by the first author) on the basis that they were similar in size, luminance and color to the spider images. When presented on the computer screen all images measured 150 mm in width and 115 mm in height. All stimuli were presented on a 17-inch computer monitor (1280 × 1080, 60Hz) connected to a 1 GHz Pentium computer. Stimulus presentation and data collection were controlled by E-Prime software (Schneider, Eschman, & Zuccolotto, 2002).

Procedure and design

Participants were tested separately in a darkened room with the experiment lasting no longer than 45 minutes per participant. The temporal bisection task was used. In an initial training phase participants learnt to distinguish between a *short* and *long* time duration (400ms and 1600ms respectively). This was achieved by first presenting a pink oval in a fixed sequence of *short* then *long*, for 8 trials. In a further 8 trials the pink oval was

displayed in a random sequence. Participants were instructed to press z to indicate *short* or m to indicate *long* (this mapping was on display throughout the experiment). During these sixteen trials participants received feedback for both correct and incorrect responses. The visual feedback lasted for 2 seconds and there was an inter-trial interval of 500ms.

During the main experimental phase, the pink oval was replaced by a spider or bird image which appeared for either the previously learnt durations (400ms and 1600ms) or an intermediate duration (600ms, 800ms, 1000ms, 1200ms or 1400ms) and participants were asked to indicate whether the image was displayed for a duration closer to the learnt *short* or *long* time duration. There were 2 blocks each comprised of 126 trials. Within each block of 126 trials there were 9 repetitions of every possible combination of stimulus type (spider, bird) and duration (400, 600, 800, 1000, 1200, 1400 and 1600). On each trial, one of the 63 bird or spider images was selected at random (without replacement) and assigned to one of these 9 repetitions. This selection procedure was repeated for the second block of trials. After completion of the temporal bisection task participants completed the SPQ (Klorman et al., 1974) questionnaires. As described in the *Participants* section, the SPQ was used to create the high fearful and low fearful groups.

Data analyses and Modelling

Hierarchical (multilevel) logistic regression

In previous research (e.g., Tipples, 2011) I estimated either logistic regression curves for each individual for each condition and then conducted a second stage ANOVA on psychophysical indices of timing[1]. Generalized linear mixed model (GLMMs) offer greater statistical precision and increased statistical power compared to the two-stage approach (Barr, 2008; Moscatelli, Mezzetti, & Lacquaniti, 2012) and therefore, I adopted the GLMM approach here. Specifically, repeated measurements were taken of the long and short responses across conditions and therefore, Generalized Estimating Equations (Liang & Zeger,

1986) with a binomial (logistic) link function were used to account for the correlation between responses (within individuals). The choice of working correlation matrix and decision to retain specific interaction terms in the model were based on the corrected quasi-likelihood information criterion (cQIC) as an index of model fit - with lower values indicating a better fit. An exchangeable matrix was selected with robust Huber/White sandwich estimators (of standard errors, confidence intervals (CIs) and p values) to safeguard against misspecification of the correlation matrix. The main effects of stimulus type (birds, spiders) stimulus duration (400, 600, 800, 1000, 1200, 1400, 1600 milliseconds) and group (low fearful, high fearful) were entered into in the model in a single step and this model was subsequently used as a baseline to test each interaction term (in sequence).

Hierarchical Drift Diffusion Modelling

To estimate drift diffusion parameters I used a Hierarchical Drift Diffusion Modelling procedure (Vandekerckhove et al., 2008, 2011; Wiecki et al., 2013) implemented in Python (Wiecki et al., 2013). In brief, HDDM uses Markov Chain Monte Carlo simulations to estimate a range of probable values for diffusion parameters – a posterior distribution of values for each parameter. The estimation is hierarchical because both subject and group level parameters are estimated simultaneously in a single model. Hierarchical Bayesian estimation is particularly suited to the type of research design used here because subject and group-level posterior estimates allowed to reciprocally influence each other leading to greater statistical precision (Wiecki et al., 2013) for research designs with a relatively small number of observations (<20) per cell of the design. A further more general advantage of Bayesian estimation is that it is possible to directly quantify uncertainty for a given experimental hypothesis by comparing the overlap between the (posterior) distributions of specific parameter estimates – a true confidence or credibility interval for an effect.

Hierarchical Bayesian regression. The central hypothesis - that for high but not low fearful individuals drifts rates would be higher for spiders compared to birds – was tested by estimating a hierarchical drift diffusion regression model for the high fearful and low fearful groups separately. Stimulus type (bird, spider) was entered as a dummy variable regressor with the bird condition serving as the baseline (or intercept) condition. To test the prediction of the model proposed by Balci and Simen - that drift rates will increase with stimulus duration - duration was entered as a continuous covariate in the regression model. The slope for duration is a direct test of the prediction that drift rates and starting point parameters will increase with stimulus duration.

Model Assessment. All hierarchical drift diffusion regression models included random intercepts for the subjects for each of the diffusion parameters (v, t, z, and a). For each fear group, model testing began by comparing an empty model (EM) that contained only random intercepts (and no fixed effects) with 2 models that increased in factorial complexity. The main effects model (MEM) included a fixed effect for both stimulus duration and stimulus type. The full model (FM) included fixed effects for both duration and stimulus type and the stimulus X duration interaction term. The Deviance Information Criterion (DIC; Spiegelhalter, Best, Carlin, & Van Der Linde, 2002) was used a criteria for assessing model fit. Although smaller DIC values indicate a better fit the reduction needs to be sufficiently large to justify an increased complexity and therefore, I used a reduction in the DIC of 10 or more as the criteria for judging improved model fit. Details of the model estimation procedure, convergence and a model adequacy are described in the *Appendix*.

Results

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Hierarchical (Multilevel) Logistic Regression. The mean proportion of long responses as a function of stimulus duration, stimulus type (birds, spiders) and group (high

fearful, low fearful) are displayed in Figure 2. To test the pacemaker-speeding hypothesis the three-way interaction between group (high fearful, low fearful), stimulus type (spider, bird) and stimulus duration was included in the model with all lower-order terms. This interaction tests whether spider fearfulness is associated with a linear increase in the proportion of long responses as the duration of spider images (compared to bird images) increases from 400 to 1600 ms – a steeper slope for spiders compared to birds in high compared to low fearful individuals. The three-way interaction was not significant (Wald Chi-Square = .336; p = .562) and moreover, the model with the interaction term did not improve model fit (cQIC = 41870) compared to the main effects only model (cQIC = 42481).

The stimulus type X group interaction resulted in improved model fit (cQIC = 41271) compared to a main effect only model. All other two-way interaction terms failed to improve model fit compared to the main effects only model. The interaction showed that high fearful individuals were, on average, more than twice as likely (OR = 2.44; 95% CI [1.68, 3.56], Wald Chi-Square = 21.90; $p < .0001$) to respond "long" to pictures of spiders compared to pictures of birds. The effect of stimulus type was absent in low fearful participants (OR = .99; 95% CI [.85, 1.16], Wald Chi-Square = .001; p = .97).

The Weber Ratio (WR) is often calculated from the slope and intercept parameters from the temporal bisection data as a standardised index of temporal sensitivity (Allan & Gibbon, 1991; Wearden, 1991). The WR for the slope for stimulus duration was .15 – a relatively low value indicating high sensitivity to changes in stimulus duration (averaged across stimulus type and group). The Bisection Point (BP; point at which participants equally often respond "short" and "long") for each stimulus type and group separately were calculated from the slope and intercept from the final model. In keeping with the two-way interaction reported above the BP indicated a shift in the psychophysical function for spiders compared to birds in high fearful individuals (spiders, high fear: BP = 805; birds, high fear:

BP = 990; spiders, low fear: *BP* = 968; birds, low fear: *BP* = 968)[1]. The latter result replicates the leftward shift in the BP for emotional stimuli recorded in previous studies (e.g., Droit-Volet et al., 2004) that used the bisection task.

Hierarchical Drift Diffusion Modelling

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Model Fit. As shown in Table 1, for both the high and low fearful groups, adding the effects of stimulus type and duration improved model fit compared to empty model. For the drift rate regression, adding the interaction term did not improve model fit for both fear groups and therefore, I proceeded to analyse the Main Effects Model (MEM). For the starting point parameter *z*, the best-fitting model differed according to fear group. Specifically, for the high but not low fearful group adding the interaction term improved model fit.

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Drift Rates. The mean response times as a function of stimulus duration for both short and long responses are displayed in Figure 3. The main hypothesis was that for high fearful individuals, drift rates would be higher for spiders compared to birds. As can be seen in Figure 4, the data support this hypothesis. For high but not low fearful individuals 95% of the probability density mass for the Spiders>Birds contrast did not contain zero (β = .34; 95% CrI = .28 to .41). Also, the Modelling results support the key prediction of the model proposed by Balci and Simen – drift rates increased linearly with stimulus duration for both the high fearful group, (β = .002; 95% CrI = .0026 to .0029) and low fearful group (β = .002; 95% CrI = .0022 to .0024).

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Starting point parameter. For the starting point parameter regression model, the results support the key prediction of the model proposed by Balci and Simen: the starting

point parameter increased with increased stimulus duration for both high fearful and low fearful individuals. Specifically, 95% of the probability density mass for the slope for duration did not contain zero for both the high fearful group (β = .00033; 95% CrI = .00031 to .00036) and the low fearful group (β = .00032; 95% CrI = .00031 to .000343). With respect to fear, the main prediction was that for high but not low fearful individuals the starting point would be higher for spiders compared to birds. The results show that for high fearful individuals the estimated Spiders>Birds contrast, (β = .084; 95% CrI = .04 to .12) was qualified by stimulus duration. The interaction effect is illustrated in Figure 5 where it can be seen that the estimated starting point parameter was initially higher for spiders (M = .43) compared to birds (M = .37) but this effect reversed in direction as the stimulus duration increased; the slope for the interaction effect was negative (β = -.000074) with an estimated reduction in the Spiders>Birds effect of .015 for every 200 ms. For low fearful participants the Spiders>Birds contrast was negative (β = -.02; 95% CrI = -.04 to -01), indicating a higher starting point for birds compared to spiders in this group.

Discussion

Drift diffusion modelling of time estimates support the main prediction that temporal information accumulates more rapidly in fear: In high but not low fearful individuals drift rates were higher for spiders compared to birds. The conclusion that fear increases the rate of temporal accumulation would have been difficult based on analyses of the choice proportion data alone because the multiplicative pattern – typically used to index rate changes in accumulation or pacemaker speeding - was absent. In short, the results highlight the value of using both RTs and choice proportion data in the context of diffusion modelling to study the effects of emotion on time perception.

The drift diffusion modelling results allow further novel insights into how fear affects timing. First, the results support the idea that fear affects time estimation rapidly because the

effect of fear on drift rates was present at shortest (400 ms) duration. In other words, evidence favouring a long decision had started to accumulate in high fearful individuals even when spiders were presented for just 400 ms. Second, analyses of the starting point parameter *z* supports the idea that increased temporal accumulation due to fear occurs during the presentation of the stimulus until the decision threshold for responding long is reached. Specifically, for high fearful individuals, the starting point was higher for spiders compared to birds at short stimulus durations but this effect reversed in direction as the stimulus durations increased beyond 1000 ms. Such a cross-over pattern makes sense if it is assumed that drift rates increased more rapidly for spiders during the initial presentation of the stimuli. An increased drift for spiders would lead to a higher starting point but once the threshold is reached as the durations lengthen and the counted pulses exceed the bisection point, the comparison process completes for spiders but not birds. For the bird stimuli, the drift rate and the starting point will continue to increase until the decision threshold has been reached. In sum, the results support the idea that the effects of fear on time perception specifically and timing more generally, follow a two-stage time-dependent sequence of processes (Balci & Simen, 2014).

The results replicate previous research and add to a growing number of studies reporting an effect of emotion on time (Droit-Volet, 2013) by replicating previous reports (Buetti & Lleras, 2012; Watts & Sharrock, 1984) of an overestimation of time for spiders in spider fearful individuals. The most recent of these studies (Buetti & Lleras, 2012) is notable because the authors were able to eliminate the effect of spiders on time estimates by manipulating perceived control. Specifically, the authors recorded a reduction in the effect for high fearful individuals when participants pressed a button to increase the occurrence of positive images Increased perceived control was illusory because positive and negative images were presented at a fixed rate (75% positive, 25% negative). The findings corroborate

previous reports (Geer, Davison, & Gatchel, 1970) of reductions in physiological arousal in response to aversive stimuli under conditions of increased control. Drift diffusion modelling can offer insight into such findings because it offers a principled way of isolating the process by which increased perceived control affects time estimates. For the results reported by Buetti and Lleras (Buetti & Lleras, 2012) visual inspection of the Bisection Points for positive images suggest that the psychophysical function for positive images shifted leftward with increases in perceived control. Such a pattern may indicate an increase temporal accumulation for positive images under high perceived control. Drift diffusion modelling could be used to test this idea.

What neural processes might support the accumulation effect reported here? A recent review (Coull et al., 2011) and meta-analyses (Wiener et al., 2010) have helped to identify a network of brain regions that increases in activity during time estimation. This network includes the supplementary motor area, basal ganglia (including the putamen and the caudate nucleus), the cerebellum and the anterior insula. According to one explanation (Craig, 2009), changes in activity in the insula cortex, due to emotion are responsible for changes in the perception of time due to emotion. In this model of time perception, subjective awareness of time arises from the sequential integration of a progression of activity from the posterior-to-mid-to-anterior insula. Such a process may map onto the increase in drift rates for feared stimuli recorded in the current research. However, it is important to emphasise that there exist other candidate regions for the accumulation effect reported here, including the supplementary motor area and basal ganglia. For example, recent studies (Dirnberger et al., 2012; Tipples et al., 2013) of the effects of emotion on time perception have recorded increased activation due to emotion during temporal process across several regions of the putative time perception network. Drift Diffusion Modelling and other cognitive modelling approaches might play important role in elucidating the functions of such regions because

cognitive modelling enables researchers to relate changes in latent cognitive processes (e.g. decision vs perceptual processes) to neural activity – it provides an intermediate level of description.

The effects of fear on time perception reported here are consistent with the idea that fear-related stimuli activate a separate system for evaluating and responding to threat. Candidate models include the fear-specific mechanism described by Öhman & Mineka (Öhman & Mineka, 2001) and the similar schema-based model of anxiety described Beck and Clark (Beck & Clark, 1997). In the schema-based model of anxiety Beck and Clark (1997) stimuli undergo 3 processing stages. In brief, the stages are 1) initial registration in which the an early-warning system evaluates the threat-value of the stimuli and if necessary prioritizes the stimulus for further processing 2) primal mode or immediate response to threat that consists of a range of physiological, cognitive, behavioural and affective responses that constitute anxiety and 3) a secondary elaboration stage in which the anxious individual evaluates the effectiveness and availability of coping resources. The effects of fear on time perception are consistent with the activation of the primal mode and in more specifically, increased arousal due to threat as the individual prepares to make a response. Here, the claim is that the effects of fear on time perception are due to the output of the primal mode stage do not directly cause anxiety. Nonetheless, the continued study of the effects of fear on time perception is likely to be valuable because time perception provides a way of studying the automatic cognitive processes described by Beck and others. The use of drift diffusion modelling furthers this objective because it enables the isolation of specific cognitive processes.

As noted in the introduction there are other models of time perception that might be used to model the effects of emotion on timing. For example, time perception has been modelled as due to: 1) the synchronisation of an internal oscillator (Jones & Boltz, 1989) or

oscillating neurons (Miall, 1989) 2) the continuous flow of information into a leaky integrator (Wackermann & Ehm, 2006) and 3) as an intrinsic property of neural networks (Goel & Buonomano, 2014). Moreover, variants of the internal clock model derived from Scalar Expectancy Theory (Gibbon, 1977) can account for performance on bisection tasks (e.g., Allan & Gibbon, 1991; Wearden, 1991). The current study was not designed to compare different models and the results do not rule out the existence of a pacemaker or other mechanism. The idea that emotion increases the accumulation of temporal information is consistent with other models of time perception including the internal clock model. In other words, the precise mechanism responsible for the effect of emotion on time perception – whether such effects are best explained by either a specific clock system or a common accumulator for the processing of both temporal and non-temporal information – has yet to be determined.

Nonetheless, drift diffusion modelling has several features that make it an attractive approach for studying the effects of emotion on time perception and also, other types of perception. First, drift diffusion modelling is a powerful approach to modelling data from two-alternative forced choice tasks because it uses all the response data - both RTs and choice proportion (or accuracy) data. Second, drift diffusion modelling is a general, neurobiologically plausible modelling approach (e.g., Shadlen & Kiani, 2013) that is not restricted to the modelling of time perception data, specifically. Finally, drift diffusion modelling has already proven useful in emotion research in helping to improve sensitive to detect effects in anxiety (White et al., 2010) and depression (Pe, Vandekerckhove, & Kuppens, 2013). In short, the future application Drift Diffusion Modelling promises rich insights into the effects of emotion on perceptual decision making.

In summary, I have provided evidence for the rapid accumulation of temporal information in spider fearful individuals and more broadly, evidence in favour of a sequential

drift-diffusion model of temporal discrimination (Balci & Simen, 2014). The results highlight the use of Hierarchical Drift Diffusion Modelling to aid understanding of the latent processes that underpin emotional psychopathology including phobia.

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Footnote

[1]For the purpose of comparison with previous research, I calculated the BP and WR following the procedure that I have used previously (e.g., Tipples, 2011) and then subjected the mean BP and WR (for the high and low fearful groups, separately) to a repeated measures ANOVA with stimulus type (spiders, birds) as the repeated measure. For high fearful individuals, there was a significant leftward shift in the mean BP for spiders (*BP* = 901) compared to birds (*BP* = 1104), $F(1, 17) = 32.59$, $p < .0001$, partial eta squared = .65 and also, worse temporal sensitivity for spiders (*WR* = .35) compared to birds (*WR* = .26), $F(1, 17) = 5.98$, $p = .02$. Inspection of boxplots indicated that the effect of stimulus type on sensitivity for high fearful individuals was due to the influence of 2 individuals with particularly poor sensitivity (*WR* > .6) – the ANOVA was no longer significant (p . 08) when the data of these individuals was removed. Exclusion of these individuals did not change the results of either the GEE analyses or the HDDM analyses and therefore, these individuals were retained for the HDDM and GEE analyses. For the low fearful individuals, all effects were non-significant ($p > .1$) with a similar mean BP for spiders (*BP* = 1088) compared to birds (*BP* = 1091) and also, a similar mean WR for spiders (*WR* = .24) compared to birds (*WR* = .24).

Table 1. Deviance information criterion (DIC) values for each fear group, for the drift rate and starting point parameter regression models. The Empty Model (EM) included random intercepts for the subjects and each of the diffusion parameters (v, t, z, and a). The fixed effects of stimulus type and duration were added to this model to create the Main Effects model (MEM). Finally, the stimulus X duration interaction term was added to the MEM to create the Full Model (FM).

	Drift rates (v)		Starting point parameter (z)	
Model	High fearful	Low fearful	High fearful	Low fearful
Empty Model (EM)	10965	10557	10965	10557
Main Effects Model (MEM)	8519	7100	10002	9310
Full Model (FM)	8513	7104	9980	9310

Figure Captions

Figure 1. The diffusion model for two-choice response times. The evidence accumulation process begins at a specific starting point (*z)* and subsequently follows an average increase or drift rate (*v)*. When the accumulated evidence reaches the upper boundary a decision is made and a response is executed. The total RT includes both the decision time and Non-decision time (T_{er}). Non-decision time consists of both stimulus encoding and response execution processes. The distance between the two decision boundaries or boundary separation (*a*) and can be used as an index of response caution (larger values index greater response caution).

Figure 2. The mean proportion of long responses as a function of stimulus duration, Stimulus type (birds, spiders) and group (high fearful, low fearful).

Figure 3. The mean response times as a function of stimulus duration for both short and long responses.

Figure 4. The mean posterior drift rate slope or difference (Spiders>Birds) for high and low fearful individuals. Error bars indicate 95% Bayesian credibility intervals (95% CrI).

Figure 5. Mean posterior estimates of the starting point parameter (*z)* as a function of stimulus type and stimulus duration for high fearful individuals.

Figure 6. Example of a model convergence plots of the trace (top left), autocorrelation (bottom left) and histogram posterior distribution (bottom right) for the fixed effect contrast Spiders>Birds.

Figure 7. The observed and predicted proportion of long responses are plotted as function of stimulus type and stimulus duration for high fearful individuals (see text for details).

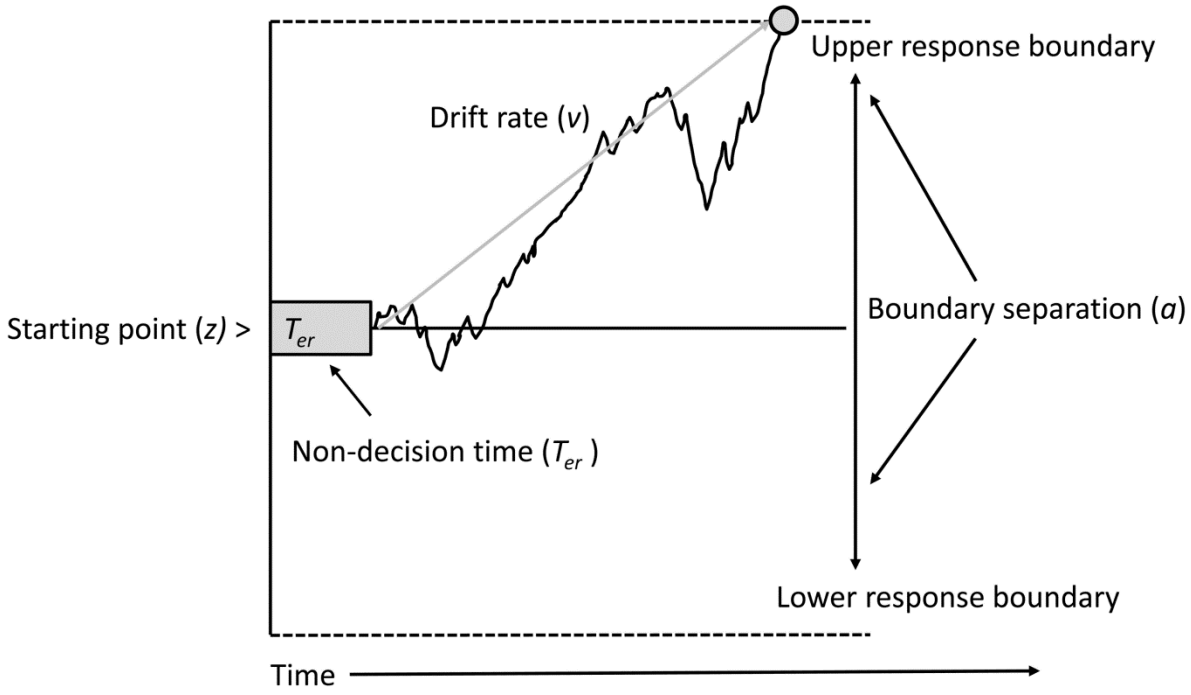
Upper response boundary
Drift rate (v)
Starting point (z) >
T_{er}
Boundary separation (a)
Non-decision time (T_{er})
Lower response boundary
Time

Figure 1.

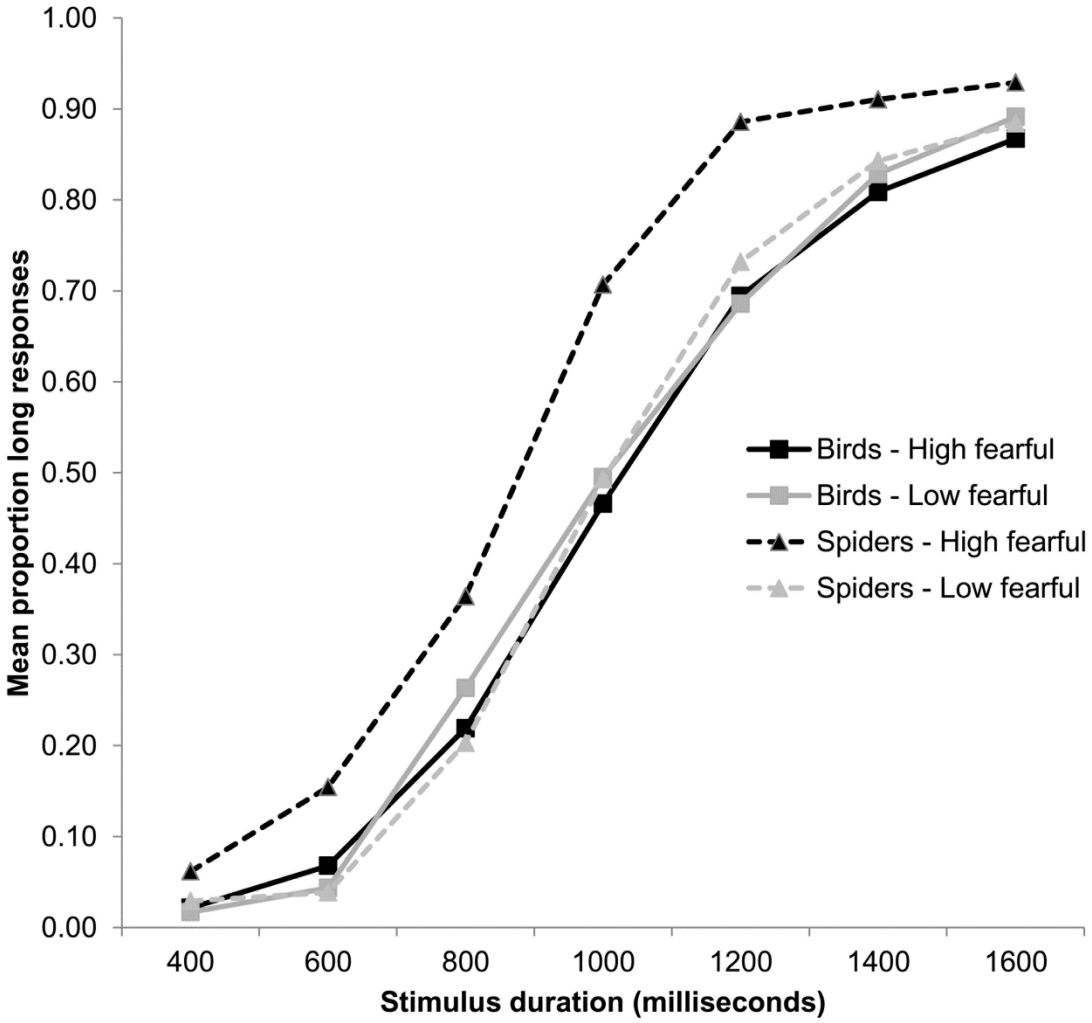
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Mean proportion long responses
400
600
800
1000
1200
1400
1600
Stimulus duration (milliseconds)
Birds - High fearful
Birds - Low fearful
Spiders - High fearful
Spiders - Low fearful

Figure 2

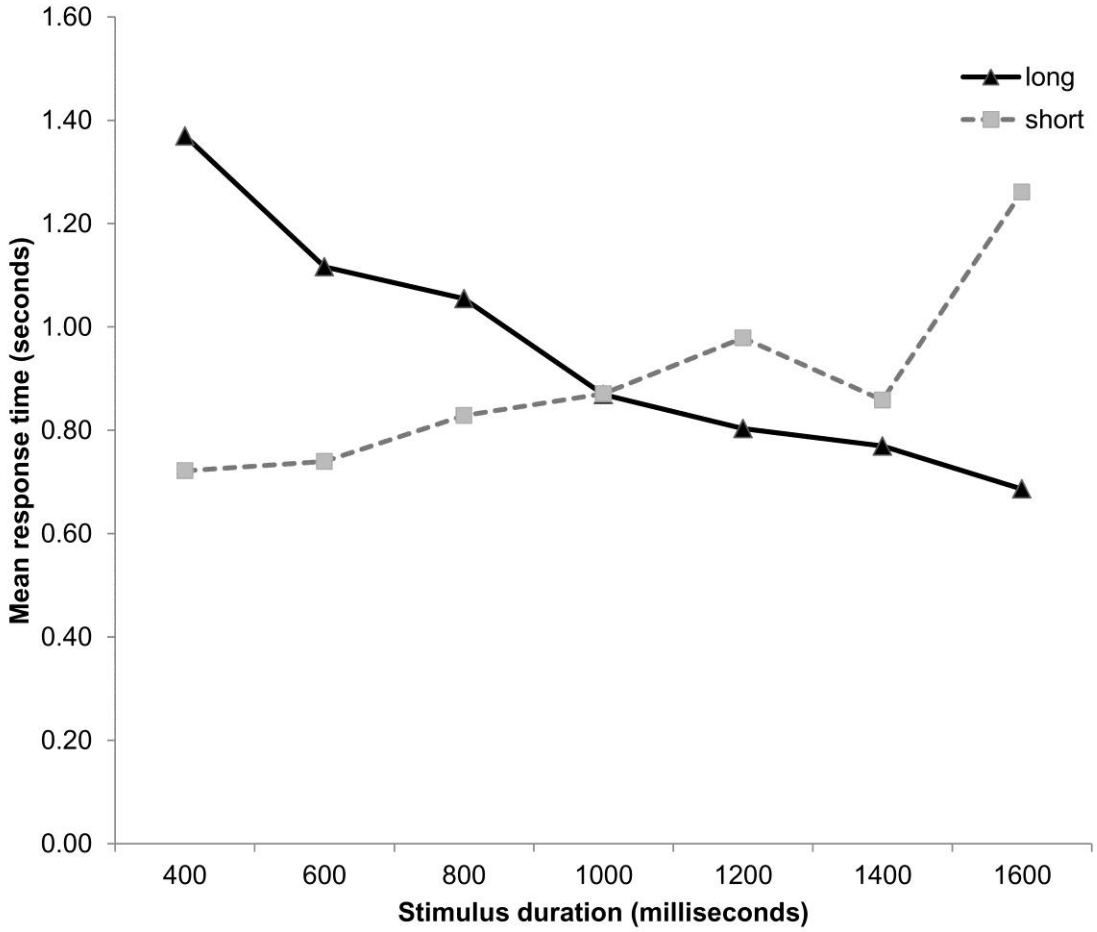
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
Mean response time (seconds)
400
600
800
1000
1200
1400
1600
Stimulus duration (milliseconds)
long
short

Figure 3

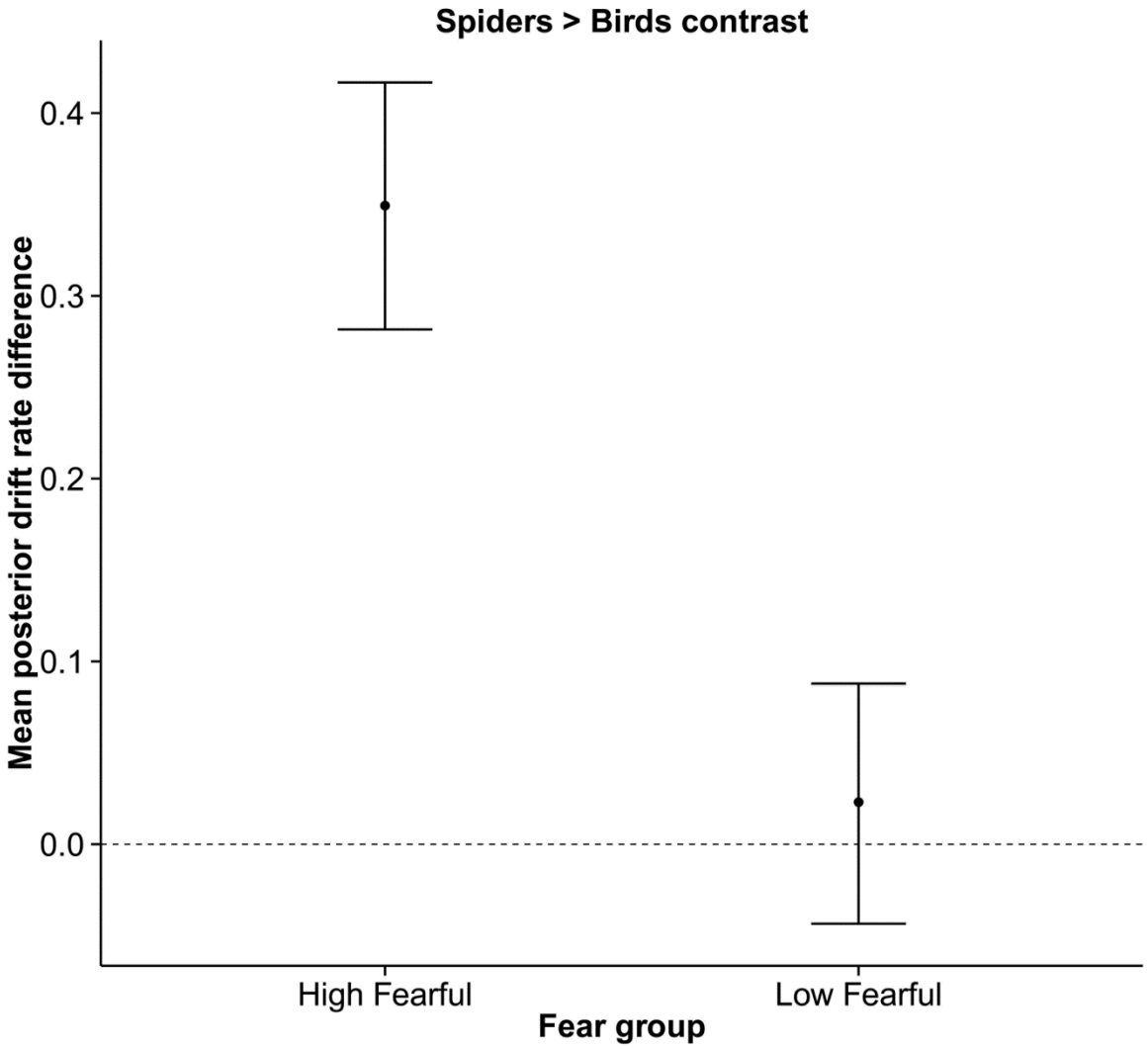
Spiders > Birds contrast
Mean posterior drift rate difference
0.4
0.3
0.2
0.1
0.0
High Fearful
Low Fearful
Fear group

Figure 4

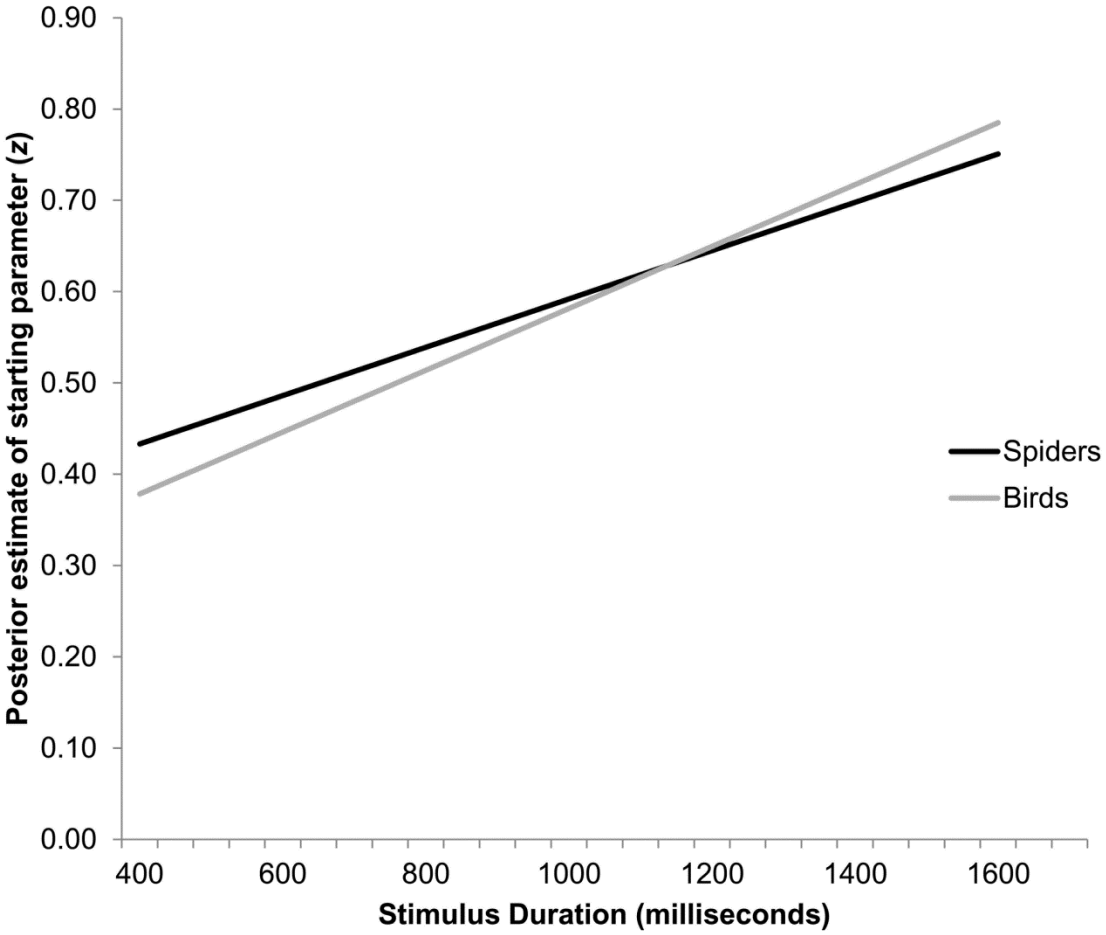
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Posterior estimate of starting parameter (z)
400
600
800
1000
1200
1400
1600
Stimulus Duration (milliseconds)
Spiders
Birds

Figure 5

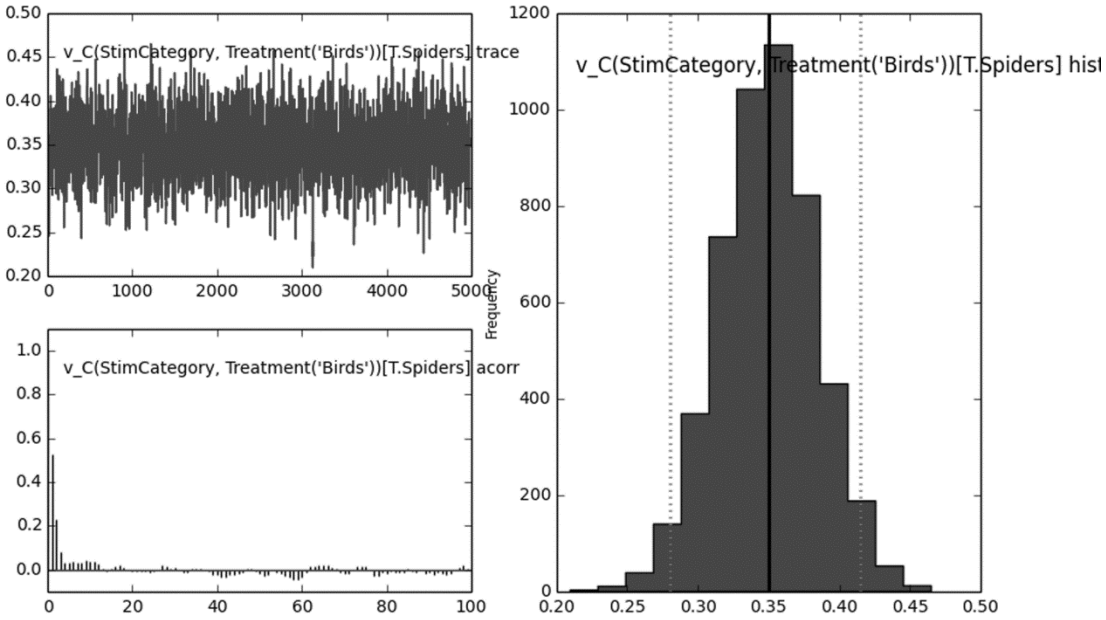
v_C(StimCategory, Treatment('Birds'))[T.Spiders] trace
v_C(StimCategory, Treatment('Birds'))[T.Spiders] acorr
v_C(StimCategory, Treatment('Birds'))[T.Spiders] hist
Frequency

Figure 6.

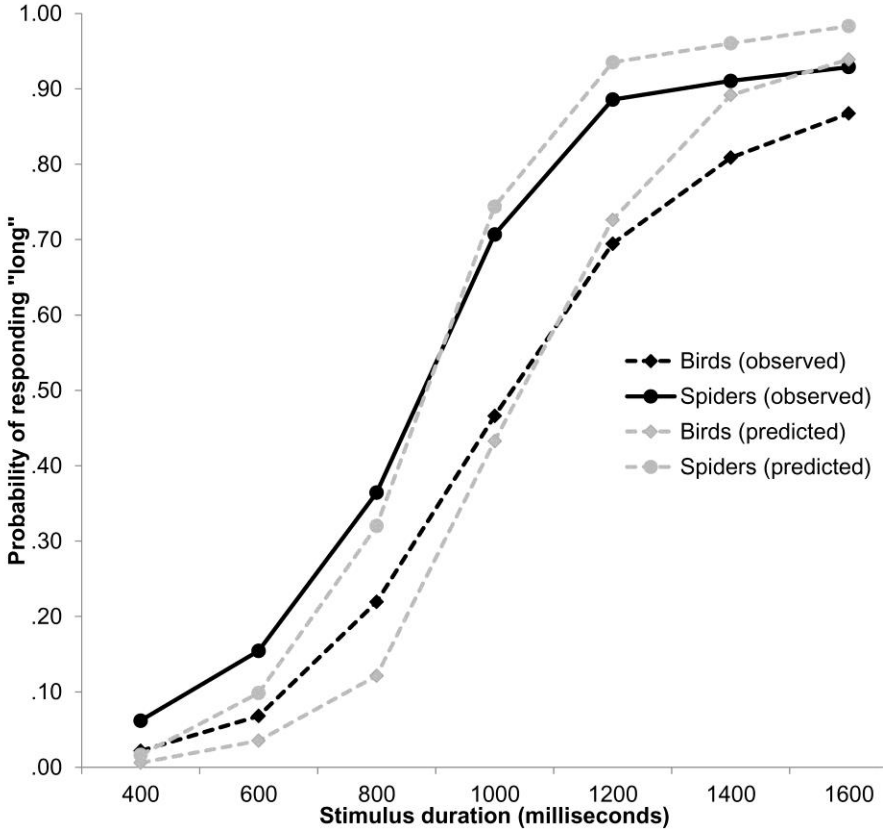
1.00
.90
.80
.70
.60
.50
.40
.30
.20
.10
.00
Probability of responding "long"
400
600
800
1000
1200
1400
1600
Stimulus duration (milliseconds)
Birds (observed)
Spiders (observed)
Birds (predicted)
Spiders (predicted)

Figure 7.

Appendix

- - - - - - Insert Figure 6 about here - - - - - -

- - - - - - Insert Figure 7 about here - - - - - -

Model estimation and convergence. HDDM is a Bayesian statistical approach and therefore, it is necessary to specify priors. Following the recommendations for HDDM (Wiecki et al., 2013) I used informative priors to constrain parameter estimates to be within the range of plausible values estimated in previous research (Matzke & Wagenmakers, 2009). Each model was estimated without assuming dependence between the drift rate *v*, and the initial bias in the starting point parameter, *z*. To assess convergence I calculated the Gelman-Rubin convergence statistic and carried out visual inspection (for each estimated parameter) of 3 plots of the: 1) trace 2) autocorrelation and 3) posterior distribution. The Gelman-Rubin statistic requires multiple MCMC runs in order to estimate the ratio of between-chain variance relative to within-chain variance. Chain stability is indicated by values close (+/− 0.01) to 1. For all models, I carried out 5 runs composed of 50 samples as a burn-in (to increase chain stability) and a subsequent 5000 iterations to estimate the posterior distribution of each parameter. For all models, the Gelman-Rubin statistic was close to 1 (+/− 0.01) and visual inspection of the 3 plots failed to reveal either 1) large jumps or asymmetry in the trace or 2) high levels (>.04) of autocorrelation (after 50 iterations) or 3) non-normality in the distribution of the posteriors. To illustrate convergence, the three plots for the contrast Spiders>Birds for drift rates are displayed in Figure 6. Figure 7 shows the results of a posterior predictive check (Chapter 6; Gelman, 2014) - an attempt to assess the adequacy of the model by comparing fitted values to the actual data. To generate Figure 7, I estimated a HDDM that included the four key parameters (a, v, Ter, and z) for each high fearful individual for each stimulus duration and stimulus type (birds, spiders). The predicted values

were estimated by drawing 500 samples from the posterior distribution of that model. The data displayed in Figure 7 are averaged across the 500 samples.